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Toward distinguishing the different types of attention using EEG signals

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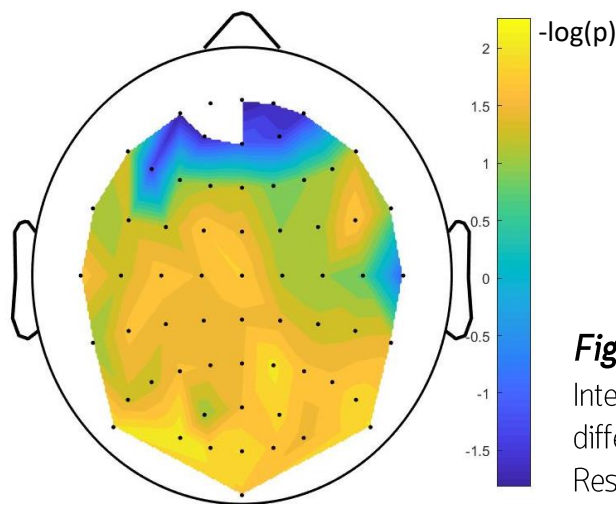
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“Attention” is a generic word encompassing *alertness* and *sustained attentions*, referring to the intensity of attention (i.e., strength), as well as *selective* and *divided attentions*, referring to its selectivity (i.e., amount of monitored information) [10]. BCI literature indicates an influence of both users’ attention traits and states (i.e., respectively stable and unstable attentional characteristics) on the ability to control a BCI. Though the types of attention involved remain unclear [1,3,4,5]. Therefore, assessing which types of attention are involved during BCI use might provide information to improve BCI usability. Before testing this hypothesis, we first needed to assess if the different types of attention are recognizable using EEG.

Hence, we asked 16 participants to perform different tasks, each assessing one type of attention presented above, while we recorded their EEG. For each task, participants had to react as fast as possible -by pressing a keyboard spacebar- to the appearance of target stimuli. The tasks and types of attention were differentiated by the type of sensorial modality of the stimuli, number of distractors, presence of warnings before the stimuli and length of the task, in accordance with the literature [2,7,8,9].

Results from the preliminary analysis tend to indicate that EEG patterns of the different types of attention are distinguishable from both one another, and the resting state’s (i.e., when participants are asked to relax and not to perform any specific task). For example, by using a Common Spatial Pattern filtering in the alpha range (8-12Hz) and a Linear Discriminant Analysis classifier, with 5-fold cross-validation we found that *sustained attention* is recognizable from the *resting state* with a classification accuracy of [55%, 92.5%] (above chance levels [62.5%, 65%] for 15 participants [6]). An inter-subject analysis of the differences of activation between these states suggested a key role of the frontal cortex (*see figure*).



Figure

Inter-subject mean significance in Power Spectral Density differences in alpha range for Sustained attention vs. Resting state (obtained using a t-test).

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